PRE-PROCESSING COMPUTER TOMOGRAPHY IMAGES FOR SEGMENTATION BASED ON REGION GROWING METHODS

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Abstract: A new method for pre-processing of computer tomography (CT) images is proposed in this paper. The method is based on down-sampling of histogram of an intensity of CT or of MR image. This helps to overcome a disadvantage of common segmentation algorithms - low contrast and blurring of interesting objects in e.g., CT images. Inaccuracy resulted from the down-sampling procedure is improved using a Markov random field model which takes into account geometrical constraints of the processed image.

Introduction

This paper introduces an image pre–processing technique intended to improve efficiency of segmentation of medical images. Segmentation is an important procedure in medical image analysis and classification especially for radiological evaluation or computer-aided diagnosis. Image segmentation refers to the process of partitioning an image into distinct regions by grouping together neighbourhood pixels based on some pre-determined using specific properties or features of pixels representing objects in the image. In other words, segmentation is a pixel classification technique that allows the formation of regions of similarities in the image [2], [4].

Many new applications of segmentation are arising with the rapid expansion of the Internet. Image segmentation methods can be broadly classified into three categories: boundary-based techniques, region-based techniques, and pixel-based direct classification methods. In practice, region-based methods are mostly used. They are typically very fast and easy to manipulate [1]. To improve performance region-based methods and their results, pre-processing techniques are usually required.

In the paper, basic theory of region-based segmentation is described. Next, the proposed pre-processing method is described in detail. Correction factor as an essential part of the method is introduced. Experiments on real computed tomography data are described and discussed in the end of the paper.

Materials and Methods

Region-based segmentation methods examine pixels in the neighbourhood based on a pre-defined similarity criterion. The neighbourhood pixels with similar properties are merged to form closed regions for segmentation. The region growing approach can be extended to merging regions instead of merging pixels to form larger meaningful regions of similar properties. Such a region merging approach is effective when the original image is segmented into a large number of regions in the pre-processing phase [4].

Thresholding is the most commonly used basic step in segmentation. It is based on expectation of homogenous regions instead of contours. It utilizes amplitude segmentation to find pixels groups of similar intensity. Such procedure can be classified as either manual, semi-automatic, or automatic depending on the segmentation application and the definition of the threshold coefficients. Particular tissues and structures in medical images usually appear in similar intensities. Therefore, thresholding technique is often applied as a feature extractor [1], [2].

Thresholding coefficients can be obtained from the image intensity histograms. It can be done manually or using algorithms searching peaks and valleys in the histogram function. The criteria how to choose appropriate coefficients depends on the segmentation application.

The pre-processing method

The new pre-processing method is proposed for segmentation of especially medical CT images of human brain. The original task defined from medical practice was to improve visibility of intracerebral hematoma in CT images for the following segmentation. The method is composed of the following steps: 1. down-sampling of image intensity histogram to reduce of number of the used gray scales, 2. correction based on Bayes approach to improve inaccurate result of the down-sampling procedure.

As a down-sampling procedure, common piecewise linear conversion function was used. The histogram

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down-sampling can be also viewed as non-equidistant re-quantization of intensity scale.

The conversion function in first iteration is depicted in Figure 1.

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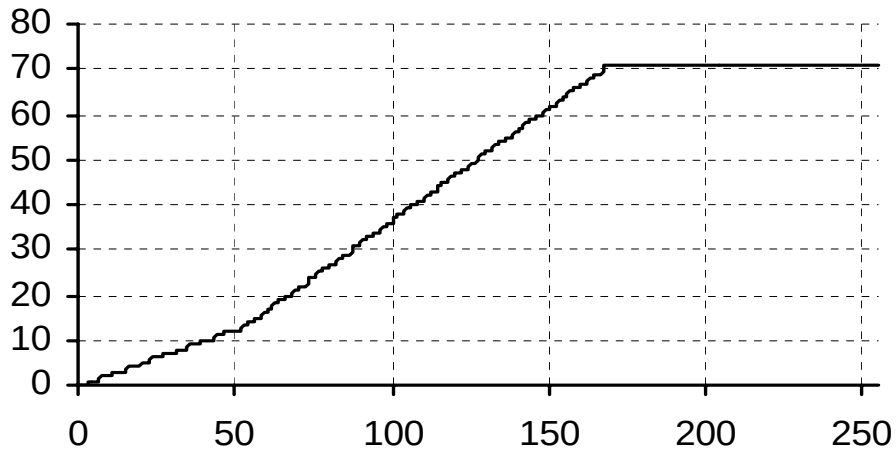

Figure 1: Down-sampling conversion function in first iteration. The main axis introduces number of levels of intensities in original image. On the accessory axis we can see reduced number of levels of intensities after down-sampling procedure. The conversion curve is not linear because we suppose *a priory* knowledge that our region of interest lies in middle part of histogram of intensities. Next parts are uninteresting and we use ruder conversion factor.

Correction factor

The result of down-sampling procedure should be corrected to improve inaccuracy. This can be done by application of a correction factor based on the following approach. *A priory* knowledge is taking in account: pixels with similar intensities are usually locally concentrated in processed images. A *conditional* probability can also be defined: if a pixel of the original image has certain intensity, it is more probable that a pixel on the same position in the resulted image has the same intensity than that the pixel in the resulted image has different intensity.

Using a modified Bayes' rule, a posteriory probability can be derived:

$$P(\boldsymbol{A}|\boldsymbol{B}) \propto P(\boldsymbol{B}|\boldsymbol{A}) \cdot P(\boldsymbol{A}) \qquad (1)$$

The first term in Eq. 1 is the *conditional* probability, the second term is the *a priory* probability. Both probabilities are usually modelled as Gibbs probability functions. This has an advantage that all variables can described directly with an image model called a Markov random field. The relation between Markov random field and Gibbs probability functions is expressed in the Hammersly-Clifford theorem [3], [5].

The states of the Markov random field are pixels x_l in neighbourhoods 3-by-3. The a priori probability expresses that pixels in which neighbouring state vectors have the same label value, are more probable than those with different values. Computation is based on a comparison of the central state with its neighbours. This can be described by equations below where $V(\boldsymbol{A})$ is a potential function defined on some neighbourhood N_l with middle state a_l and neighbourhoods states a_j. Example this neighbourhood is on Figure 2. The *a priori* probability is thus:

$$P(\boldsymbol{A}) = \frac{1}{Z} \cdot \exp(-V(\boldsymbol{A})) \quad with \quad V(\boldsymbol{A}) = \sum_l V_{N_l}(\boldsymbol{A}) \qquad (3)$$

$$V_{N_l}(\boldsymbol{A}) = \sum_{x_j \in N_l} V_{l,j}(a_l, a_j) \qquad (3)$$

$$with \qquad V_{i,j}(a_i, a_j) = \begin{cases} -\gamma & \text{if} \quad a_j = a_i, \\ +\gamma & \text{if} \quad a_j \neq a_i. \end{cases} \qquad (4)$$

where γ is a constant.

More details about Bayesian image analysis can be found in [3] and [6].

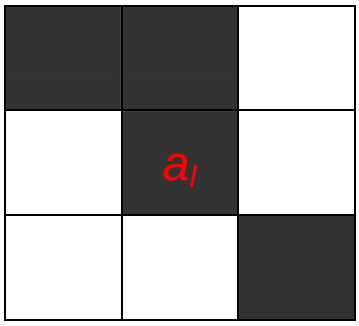

Figure 2: Neighborhood N_l centered on image pixel value a_l.

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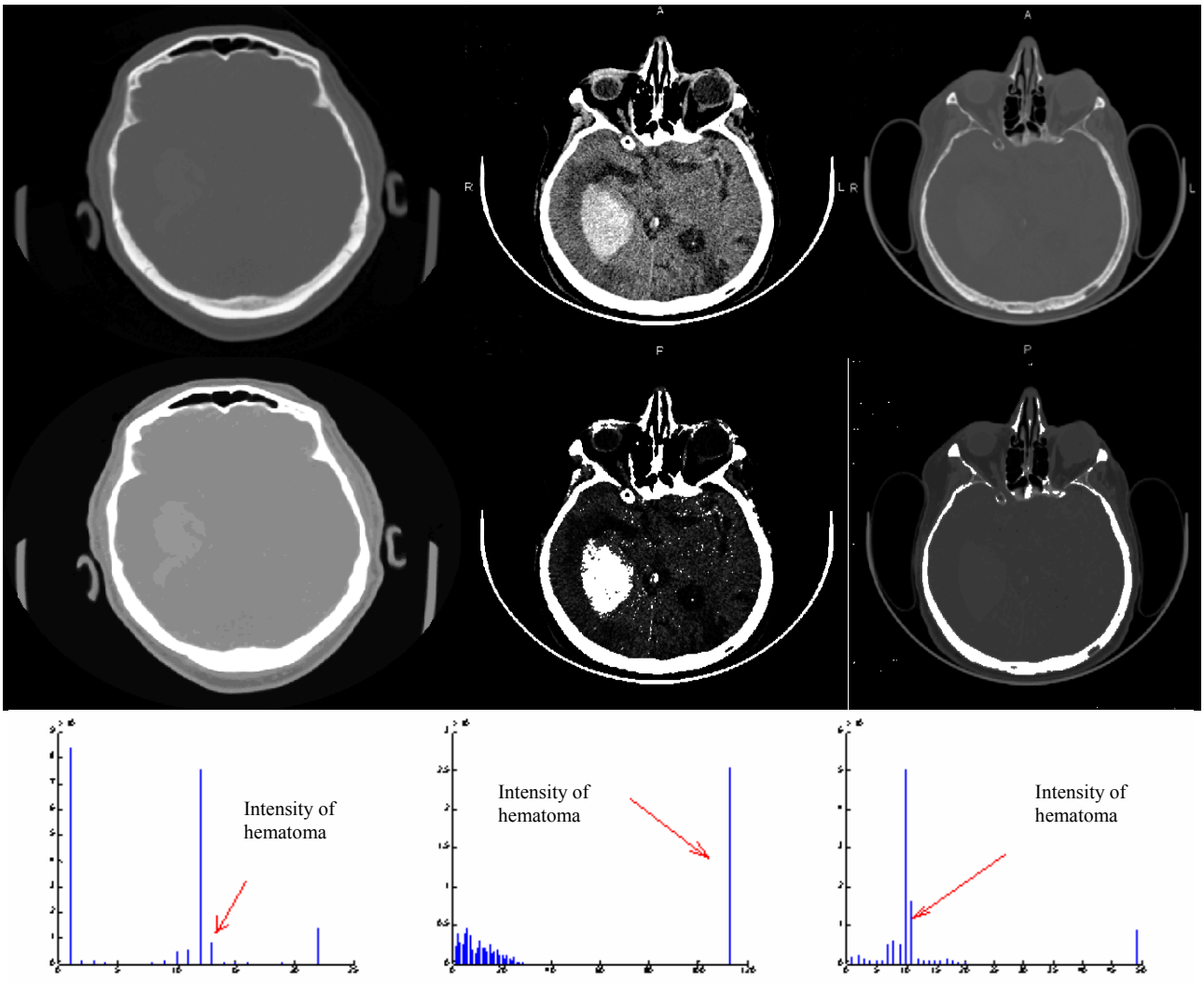

Figure 3: Pre-processing of a CT image of human brain with intracerebral hematoma. From up left to bottom right: original CT image (255 gray scales, skull window), original CT image (256 gray scales, tissue window), the same slice CT image with 255 gray scales in skull window, middle panel: resulted CT image (22 gray scales, skull window), resulted CT image (114 gray scales, tissue window), resulted CT image (49 gray scales, skull window), bottom: histograms of intensities for resulted images in middle panel: histogram of intensities for skull window, histogram of intensities for tissue window and histogram of intensities for next skull window. Details borders of hematoma are on Figure 4

Results

The pre-processing method was tested with two different sets of human brain CT images with intracerebral hematoma present in left hemisphere. The images were coded to 512 x 512 pixel bitmaps with 256 level gray scale and thereafter pre-processed.

Down-sampling procedure described in Section Material and methods was applied in a multiple steps – iterations. Then, a correction factor described in same Section was added to improve the result of pre-processing. Each of neighbourhood pixel is taken with same weight of in signification.

Figure 3 present results of the proposed method. The first line in this Figure introduce input images from two different sets (first set is presented only skull window and second set is presented both basic windows for comparison). In second line are presented resulted images after pre-processing and in third line are histograms of intensities of resulted images for introducing set of thresholds for segmentation.

The pre-processing software was tested in 1.6 GHz Pentium Centrino-based computer with 512 MB memory, running under program MATLAB 7.0 with selected libraries in C language. The pre-processing process takes about 7 sec per slice for images with size 512 x 512 pixels and with 256-level gray scales.

Discussion

Figure 3 presents results of the three iterations of the proposed method. First line of images shows the

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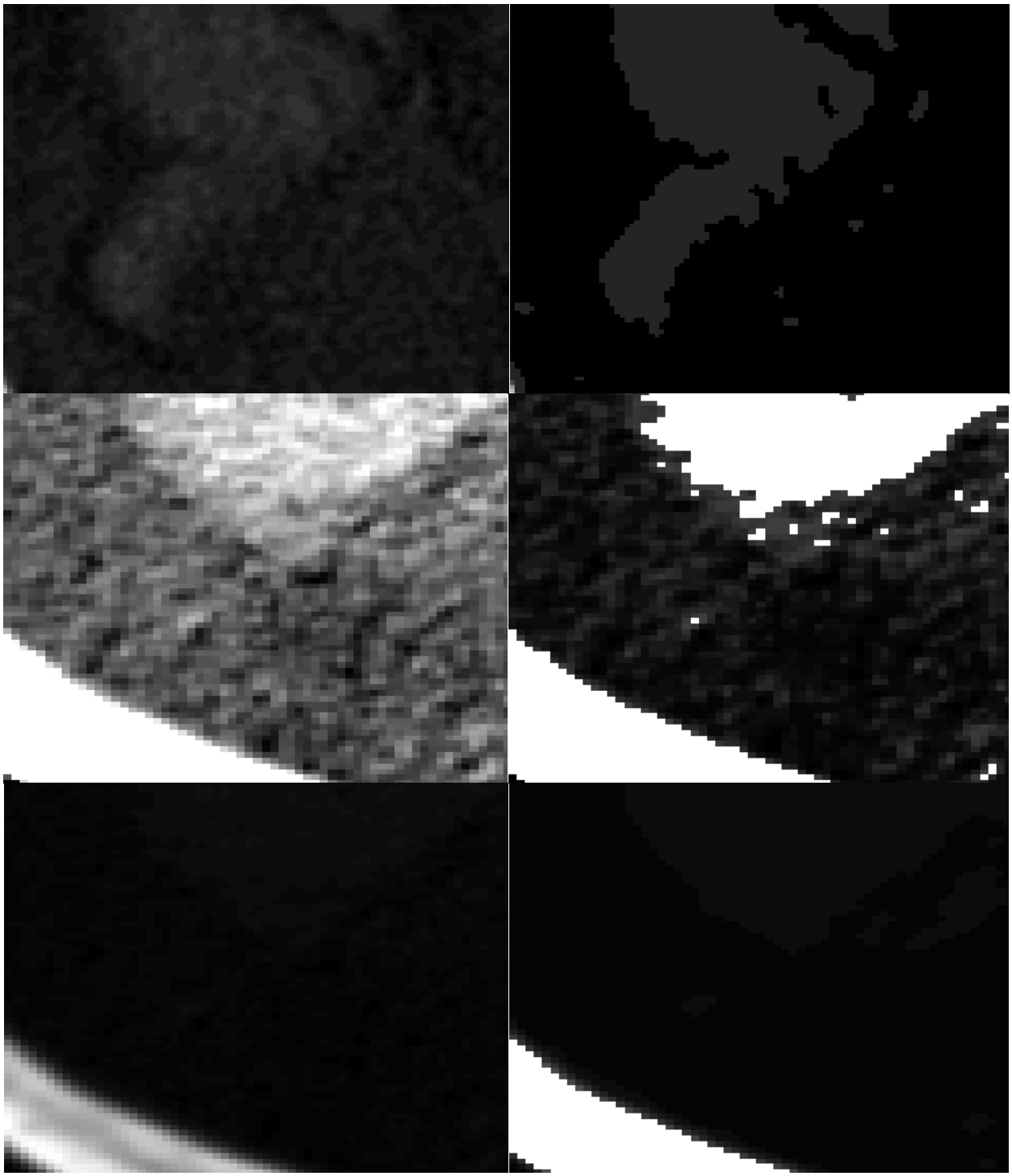

Figure 4: From top to bottom: Details of original and resulted images from the first set in Figure 3 (skull window), details of original and resulted images from the second set in Figure 3 (tissue window), details of original and resulted images from the second set in Figure 3 (skull window)

original image with indication of intracerebral hematoma in left hemisphere from two sets. One can see that hematoma region is better visible after pre-processing than in original image. Pixels introducing intracerebral hematoma have same intensities through whole hematoma region. The resulted image (for the first set) has only 32 gray levels which make an advantage for classical segmentation method based on thresholding or region growing. Resulted images for the second set of images have more gray levels (115 gray levels for tissue window, 49 for skull window) but peak which present pixels of intensity of hematoma, is clearly visible (we can see it on the third line of Figure 3. Therefore we can use classical methods for

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segmentation too. After fourth iteration, most information is lost and the images have no significant result (in case of skull windows).

The proposed pre-processing method down-samples an image histogram for spreading important features to same intensity in CT image. However, some information is lost in this process therefore Bayes approach was applied to improve resulted inaccuracies.

Conclusions

The proposed method exploits down-sampling of histogram of intensities for pre-processing. This generates some inaccuracies that can be corrected using Bayes approach.

The presented method brings significant advantages for the image analysis: 1. the regions of interests are more visible, 2. the resulted image is composed using less gray scales which makes the following segmentation easier.

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